# optim\_functions

These functions are for the optimization process.

Model parameters appearing here are better described in CMV\_Models.pdf documentation. The optimization procedure proceeds as follows:

- 1. a model (passed as a function) and parameters (fixed and to be optimized) for the model are passed into the nloptr wrapper (nloptr\_call) directly from a specific model fitting script (they are randomly drawn using LHS). Parameter constraints are applied to the solver call if they are given.
- 2. nloptr\_call calls nloptr::nloptr with appropriate settings which optimizes optimize\_fun and passes in the model function and parameters (fixed and to be optimized).
- 3. If the parameters result in a very large R0, then the model simulation fails. So there is a check for this that returns an mse = Inf. I think this might be legacy code because the LHS code accounts for this by limiting the range of beta.
- 4. The model is simulated with desolve::lsoda.
- 5. Oscillatory results (highly periodic simulations that go through every day point) are heavily penalized by given mse of Inf.
- 6. optimize\_fun calls cost\_function passing model simulation results and infant episode data. Model simulation results are compared to viral data at common points using least squares. least squares calculation is returned.

Initial value note: This version is written with intention that  $I_0 = 1$  (initial infected cells with replicating virus) and the start\_day (before data) is fitted. start\_day works by having the model start simulation at -start\_day, so that day 0 in the model is day 0 in the data (first positive). For other initial values,  $S_0 = K$ ,  $I_0 = 0$  (the latently infected compartment, would be  $I_0$  in manuscript),  $I_0 = 0$ , and  $I_0 = 0$  ( $I_0 = 0$ ) in the manuscript).

The initial virus settings are from legacy code and it is not advised to fit the initial viral load (before detection) at a fixed start time. AUC\_data is also legacy code for a different implementation of immune response. It is effectively equivalent to setting  $\gamma$  (called 'death' in CMV\_Models.R) = 0 (see CMV\_models.pdf).

## **Functions**

#### 1. nloptr call

fit = nloptr(

wrapper for nloptr. Has two separate calls depending on if bounds are specified. Also post-processing of output include de-logging fitted values and returning a simple data frame that may (justParms = F) or may not (justParms = T) include fit information.

```
x0 = fitted_parms,
    eval_f = optimize_fun,
    opts = list("algorithm"="NLOPT LN NELDERMEAD",
                "xtol_rel"=1.0e-8, "maxeval" = maxeval),
    model_fun = CMV_model, inData = fit_data,
    inParms = fixed_parms, init = model_initial, AUCData = AUCData,
    parmNames = names(fitted_parms), RO_test = RO_test)
}
else{
  fit = nloptr(
   x0 = fitted_parms,
    eval_f = optimize_fun,
    lb = unname(lowerBounds),
    ub = unname(upperBounds),
    opts = list("algorithm"="NLOPT_LN_NELDERMEAD",
                "xtol_rel"=1.0e-8, "maxeval" = maxeval),
    model_fun = CMV_model, inData = fit_data,
    inParms = fixed_parms, init = model_initial, AUCData = AUCData,
    parmNames = names(fitted_parms), RO_test = RO_test)
parmsfit = 10^fit$sol
names(parmsfit) = names(fitted_parms)
outparms = c(parmsfit, fixed_parms)
fit output = as.data.frame(t(outparms))
#default to include additional fit information
if(!justParms){
  fit_output$mse = fit$obj
  fit_output$conv = fit$status
fit_output
```

### 2. optimize\_fun

called by nloptr for optimizing the fitparms. Can be called independently. R0\_test uses crude test of R0 as a boundary for bad parameters to avoid weird fits (R0 < 88). This also checks for highly oscillatory fits by penalizing models that peak within 5 days.

```
init["S"] = as.numeric(unname(parms["K"]))
  init["I"] = as.numeric(unname(parms["initI"]))
  init["V"] = as.numeric(unname(parms["initV"]))
  start_time = -round(unname(parms["start_day"]), 1)
  times = seq(start_time, max(inData$days2) + 50, 0.1)
  # this throws out parameters that have RO > 100, this is the old RO and is missing (1+mu/alpha) in de
  # so the actual constraint is > 82 since mu = 1/4.5 and alpha =1, that term =1.22
  # so when this RO equals 100, the actual RO is 100/1.22 - 81.97
  if(RO_test) if(with(as.list(c(fitParms, inParms)), (beta * K * p /(delta * c))) > 100) return(Inf)
  model_out = as.data.frame(lsoda(init, times, model_fun, parms, AUCData = AUCData))
  if (sum(model_out$V) == "NaN" | dim(model_out)[1] != length(times)) return(Inf)
  #if there is early oscillation
  if(model_out$time[which.max(model_out$V)] < 5) return(Inf)</pre>
  mse = cost_function(model_out, inData)
  if (mse == 0) return(Inf) # browser()
  return(mse)
}
```

#### 2b. optimize\_fun\_test

Use this with results to calculate mse (generally for troubleshooting)

## 3. cost\_function

mse function using simulated model data and raw data. Called by optimize\_fun but can be called independently.

```
cost_function = function(model, data, debug = F){
  if(debug) browser()
  data = arrange(data, days2)
  data = data %>% dplyr::mutate(days_model = days2)

sample_model = arrange(model[which(round(model$time, 1) %in% round(data$days_model, 1)), ], time)
  mse = sum((log10(sample_model$V) - data$count2)^2, na.rm = T)
  if (mse == "NaN") browser()
  #print(mse)
  return(mse)
}
```